MRI Registration Algorithms

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Abstract

MRI registration algorithms are used to convert data from MRI scans into three-dimensional segmentations of the brain. VoxelMorph is a registration method developed by researchers at MIT and Cornell University which utilizes a convolutional neural network to treat the image mapping function parametrically. This algorithm produces results that are consistently as accurate, and in some cases more accurate, than conventional approaches to medical image registration. It also does all of this significantly faster, especially when using a GPU to run it. The impact of this quicker speed could be important, but also the application of convolutional neural networks as a way of improving older processes is an important factor. VoxelMorph is a much quicker and equally accurate MRI image registration method, and is pushing the medical community forward by implementing a CNN to accomplish this task.

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Introduction

Magnetic Resonance Imaging is a procedure often used in the medical field which maps out data gathered about the human brain into a visual format, assisting professionals in treating and diagnosing a variety of ailments. The process is mostly computerized, and requires the use of algorithms to convert the raw scan data into a processed image of the different segmentations of the brain. Over the years there have been many improvements to these algorithms, utilizing technological advancements to improve speed, accuracy, and functionality. As the algorithms become refined and more complex, the ability of doctors to identify irregularities in these scans goes up. MRIs are very common procedures which are used on many people, so the improvement of it can have a significant impact on everyone, not just the professionals who utilize them. VoxelMorph, a Convolutional Neural Network algorithm is a much more efficient and optimized way to compile MRI scan data when compared to split and merge segmentation algorithms such as csFCM, the application of which will greatly decrease medical imaging processing times, and improve accuracy of three-dimensional scans. Using research conducted through MIT and Cornell University, it can be shown that using a CNN will drastically improve this image registration, benefitting the medical community at large, along with those who receive MRI scans utilizing this newly developed algorithm.

Background

The processing of MRI scan data has been implemented in varying fashions for decades, with one of the early methods being Split and Merge Segmentation. The process of segmentation is important in medical images, as it is used to define boundaries of similarly characterized regions. Often to distinguish in MRIs the areas containing grey matter, white matter, and cerebrospinal fluid. The locations, amounts, and intensity of such regions are important to identifying potentially diseased regions, and getting the subject the help that they need. This information is all so important because, by increasing the details and information contained within the scanned image registration doctors are able to identify potentially life-threatening issues, such as Alzheimer's or Multiple Sclerosis. Doctors can use factors relating to proportions of matter, and location of different plaques in identifying these, so as the image registration technology advances, it directly effects the ability to detect these horrible diseases as early as possible. One common issue with registration methods, is the introduction of noise to the images. Noise is referring to irregular patterns of brightness and pixel information in the pictures, which obscure the data that could be helpful to professionals. Reducing noise is an important aspect of improving the techniques used. Medicines can also be created to specifically target regions of the brain based on the information extrapolated from higher quality medical images. This paper will also discuss the use of Convolutional Neural Networks(CNN) to train a registration model for medical images. CNN's are effectively a representation of the way a human brain works, with connections between neurons known as synapses. CNN's are able to be trained with a learning model to have connections between certain neurons, and then be able to apply an intelligent task based on these mappings. The creators of VoxelMorph have utilized this tool to enhance the quality, and speed of their registration model, by treating the data as a parametric function. This is just another improvement of the likely many to come in the future for MRI image processing.

Precedents & Related Works

Researchers have been improving the algorithms used to register these images from MRI scans for years, with one of the major segmentation techniques being called Fuzzy c-means clustering. This strategy to identify regions of brain matter approaches each pixel of the image as related to its surrounding pixels, rather than by simply measuring the intensity of the matter at that point. In 2015, researchers from Jadavpur University in India, improved this by adding conditional variables based on spatial information, to further clarify the subject matter, and increase details regardless of present image noise (Adhikari, 2015). The new version of Fuzzy c-means clustering was called csFCM for conditional spatial Fuzzy c-means clustering. Another way that researchers have improved Split and Merge segmentation, though done around 20 years ago, was to use homogeneity criteria in order to determine the smallest number of regions, thus more accurately matching the realistic boundaries of these areas. This application to three-dimensional scans better allows doctors to view patient's lateral brain ventricles, helping them to identify signs of Alzheimer's and track the development of Multiple Sclerosis, among many others (Manousakas, 1998).

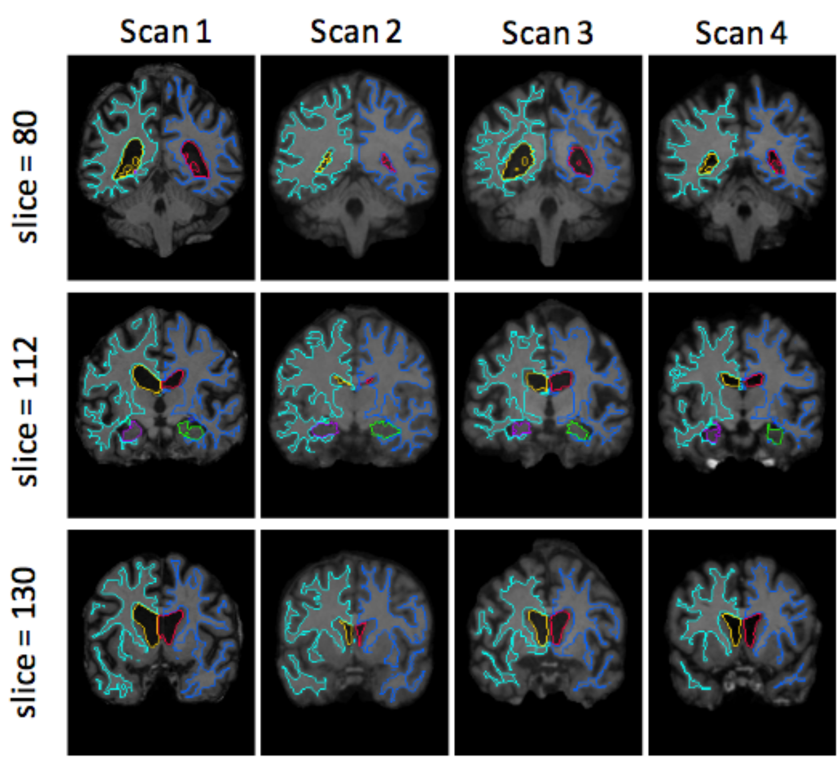

Figure 1. Example of slices from three-dimensional MRI scan. Each color represents a different region of interest to medical professionals.

Support

VoxelMorph

Researchers from MIT and Cornell University presented their medical image registration algorithm called VoxelMorph at the 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, in the paper *An Unsupervised Learning Model for Deformable Medical Image Registration*. This research was conducted by Adrian Dalca, John Guttag, Mert Sabuncu, Amy Zhao, and Guha Balakrishnan (2018) under MIT professor Bill Freeman. Their novel approach to three-dimensional medical image registration relies on treating the registration methods as parametric functions, and utilizing a CNN to teach the program how to handle it in this way (4.1 Balakrishnan, 2018).

The purpose of their paper is not only to introduce this new technique for handling image registration, but also to perform an analysis comparing the results from it to those from other current techniques being used for the same purpose. The researchers performed tests on VoxelMorph alongside Symmetric Normalization (SyN) from the ANT software package, as well as against the regular affine linear correspondence method. For reference, VoxelMorph uses a non-linear correspondence between voxels within its registration method. Another aspect the researchers evaluate is the effectiveness of having different size decoders, and using fewer channels in the layers. They distinguish these changes by separating VoxelMorph-1 (VM1) and VoxelMorph-2 (VM2) (fig. 2), the latter being the method using more channels in the final three layers, as well as having a larger decoder. These specific differences are noted in fig. 3 (p.9255 Balakrishnan, 2018) showing that VoxelMorph-2 has 13 three-dimensional volumes compared to VoxelMorph-1's 12 volumes. The second and third to last volumes in VM2 also have 16 channels each, with one and two layers respectively as opposed to VM1's second to last volume containing two layers of eight channels.

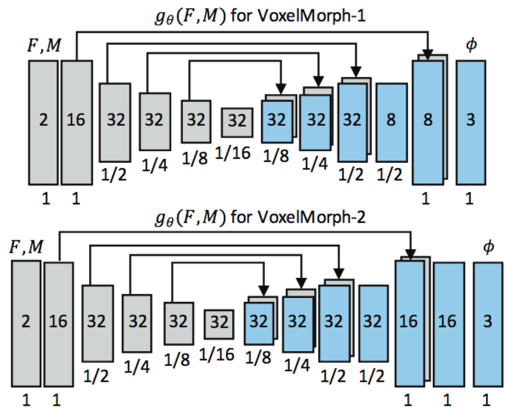

Figure 2. A three-dimensional volume is indicated by each rectangle with the number of channels contained inside.

The tests conducted on these four different implementations of three-dimensional medical image registration are assessed based on their performance given sample sets of MRI scans. The researchers use 7829 scans from publicly available databases: ADNI, OASIS, ABIDE, ADHD200, MCIC, PPMI, HABS, and Harvard GSP (p. 9256). The ages and health of the subjects within these scans vary widely, especially between the datasets thus giving the researchers a diverse array of conditions to test for robustness. The method used for "obtaining dense ground truth registration for these data" is called a Dice score (p. 9256).

Dice scores are calculated using a formula given the sets of voxel structures for fixed and moving images of a certain structure 'k' being two times the union of the two sets over the sum of their absolute values. This equation results in a score between zero and one, with zero meaning that there is no overlap between the two structures, and one indicating that they are identical (p. 9256).

Table 1

Average Dice Scores and Runtime Results for Affine Alignment, ANTs, VoxelMorph-1, VoxelMorph-2.

Method	Avg. Dice	GPU sec	CPU sec
Affine only	0.567 (0.157)	0	0
ANTs	0.749 (0.135)	-	9059 (2023)
VoxelMorph-1	0.742 (0.139)	0.365 (0.012)	57(1)
VoxelMorph-2	0.750 (0.137)	0.554 (0.017)	144 (1)

Using these methods, they found Affine to have an average dice score of 0.567, ANT's SyN to have a score of 0.749, VoxelMorph-1 with a score of 0.742, and VoxelMorph-2 with a score of 0.750. The other aspect which was tested for in this experiment is the runtime in seconds when utilizing a CPU versus a GPU. CPU or central processing unit is the hardware part of a computer which performs most calculations using transistors and logic gate architecture, while the GPU or graphics processing unit is more designed to perform very simple calculations, such as geometry, but an order of magnitude faster and to concurrently solve many simple problems like this. The researchers use an Intel Xeon E5-2680 CPU which is a high-end server CPU meant to handle heavy usage loads, and an NVIDIA TitanX GPU, which is also a high-end hardware unit designed for intense loads. They do not however test runtime on the affine method because it is constant amongst all of the four registration algorithms being studied. For CPU runtime on ANT's SyN, it took 9059 seconds with a standard deviation of 2023 seconds. This is much longer compared to VoxelMorph-1's CPU time of 57 seconds with standard deviation of one second and VoxelMorph-2's time of 144 seconds with standard deviation of one second as well. The interesting aspect of this test presents itself when the GPU time is tested. There are however no GPU implementations of SyN, so it has been left out of this bracket along with affine. VoxelMorph-1 scored an average GPU time of 0.365 seconds and VoxelMorph-2 scored 0.554 seconds. Both of which have a standard deviation of less than .02 seconds (p. 9257).

These results are extremely relevant and show that VoxelMorph does indeed perform the same action in a quicker manner. The results of the Dice score comparisons show us that VoxelMorph gives us just as accurate a representation as other top methods using its registration method, if not a more accurate one. VoxelMorph-2 has a .001 higher Dice score than ANT and VoxelMorph-1 is only beneath ANT by .07. These are extremely close values showing that there is no loss in accuracy when using this method. What is truly amazing is that these same results are achieved nearly 20,000 times faster when using a GPU.

Societal Relevance

Now that we have discussed the benefits of using VoxelMorph over other algorithms like SyN, we can start to understand the implications this has beyond technical improvements. Although VoxelMorph does not appear to improve the quality or accuracy of image registration it does keep the same high level of quality which is expected of any implemented registration method. Preservation of quality and detail in medical images is of the utmost importance. These details can make the difference between diagnosing an illness or tracking the developmental progress of a tumor rather than not being able to tell.

The VoxelMorph team show that utilizing a convolutional neural network can be greatly beneficial in improving a medical process. This raises the question of what other processes might benefit from implementing a convolutional neural network in some way. Since MRI processing times could be decreased by hours, resources such as energy, man power, and computational power are free to be used for other purposes. Although it does not seem like this benefit will greatly impact everyday people receiving MRI scans, it does mean that waiting times could be decreased, treatments could be figured out faster, and emergency situations could be recognized much sooner, potentially saving a person's life. If a convolutional neural network were to be applied to other common medical diagnostic tests, total waiting time could be drastically cut back. Waiting to find out the results of important tests can be one of the most stressful times in a person's life, and doctors recognize the side effects that stress may have on a debilitating condition (Hoffman, 2012). Removing or improving this aspect of the medical field in general is priceless.

An example of a CNN drastically improving an area of study is when they are applied to detect perivascular spaces. As shown in Figure 3, Researchers from the University of Seoul and University of North Carolina at Chapel Hill have shown that a convolutional neural network can be used to effectively increase the detail surrounding perivascular spaces which are used to detect many degenerative brain conditions (Jung, 2019). This shows that using convolutional neural networks can directly lead to a benefit for patients and doctors.

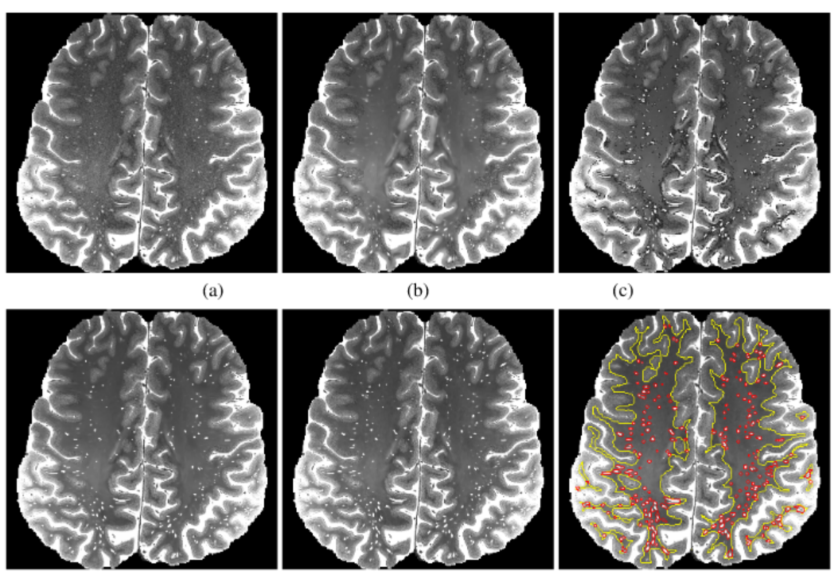

Figure 3. Comparison between (a) original image, and (f) proposed enhancement with outlines for relevant perivascular spaces.

Ethical Analysis

When determining the moral value of something, ethicist John Stuart Mills argues on behalf of the ethical philosophy Utilitarianism. This method of thinking values whichever action brings about the most amount of use, benefit, or utility to the greatest amount of people possible. That is, the morally right action can be determined as the one which derives the most overall happiness and pleasure, and the least amount of pain. If VoxelMorph were to be implemented, the benefits and utility can be measured as the additional resources that are made available for other uses in medical facilities where MRI scans often take place. These benefits could take the form of power consumption being reduced, effectively lowering the operating costs of the facility, as well as contributing to the battle against one's own carbon footprint. As has been shown, there are only benefits, and no recognizable disadvantages resulting from creating an equally accurate, yet much more efficient approach to MRI image registration. Thus, John Stuart Mill, as a Utilitarian, would agree that VoxelMorph presents more value than traditional approaches. Another doctrine which could be used to analyze this situation is Deontology, the philosophy which Immanuel Kant utilizes in his writings. Kant argues that moral worth in actions are determined not by the outcome, as a Utilitarian would maintain, but instead by the intent behind the action. Specifically, the intent, Kant argues, must be that the action is done out of one's duty. As professionals in the software engineering field, according to ACM SE Code of Ethics section 6: Profession, it is our responsibility(duty) to advance the integrity and reputation of the profession. Section 3: Product also states that we shall as professionals, ensure our products meet the highest professional standards possible. Medical professionals also have some degree of duty to their patients to allow them access to the highest standard of care, which could be found in implementing VoxelMorph for MRI image registration. Therefore, Kant would also see that VoxelMorph has value, and should therefore be implemented, but only because it is the duty of professionals to do so.

Conclusion/Summary

Overall the benefits of using VoxelMorph for medical image registration are clear and abundant. They greatly increase the speed at which data can be processed, from a few hours to less than a second, all the while maintaining the same high standard level of quality and detail when compared to other currently-used algorithms. This algorithm uses a convolutional neural network to approach the problem, which should be utilized more often in other areas of research. It has been shown that convolutional neural networks can drastically improve many aspects of an algorithm's functionality. It is for this reason that professionals in the computing industry should consider using convolutional neural networks as a tool for solving other issues. It is the responsibility of such professionals to continually improve and innovate on past technologies, and convolutional neural networks have shown themselves as a particularly effective tool for accomplishing such a feat.

References

Adhikari, S. K., Sing, J. K., Basu, D. K., & Nasipuri, M. (2015). Conditional spatial fuzzy C-means clustering algorithm for segmentation of MRI images. *Applied Soft Computing, 34*, 758-769. doi:10.1016/j.asoc.2015.05.038

Balakrishnan, G., Zhao, A., Sabuncu, M. R., Dalca, A. V., & Guttag, J. (2018). An unsupervised learning model for deformable medical image registration. *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*. doi:10.1109/cvpr.2018.00964

Boyden, E. (June 2016). *A New Way to Study the Brain's Invisible Secrets* [Video file]. Retrieved from https://www.ted.com/talks/ed_boyden_baby_diapers_inspired_this_new_way_to_study_the_brain

Hoffman, J. (2012, July 23). The anxiety of waiting for test results. https://well.blogs.nytimes.com/2012/07/23/the-anxiety-of-waiting-for-test-results/

Jung, E., Chikontwe, P., Zong, X., Lin, W., Shen, D., & Park, S. H. (2019). Enhancement of perivascular spaces using densely connected deep convolutional neural network. *IEEE Access, 7*, 1-1. doi:10.1109/access.2019.2896911

Manousakas, I., Undrill, P., Cameron, G., & Redpath, T. (1998). Split-and-Merge segmentation of magnetic resonance medical images: performance evaluation and extension to three dimensions. *Computers and Biomedical Research, 31*(6), 393-412. doi:10.1006/cbmr.1998.1489